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User Modeling Of Online Consumers: Between-Gender Differences In Click Path Data

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USER MODELING OF ONLINE CONSUMERS: BETWEEN-GENDER DIFFERENCES IN CLICK PATH DATA

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Abstract

Given people's differences in preferences, personalities, or demographic factors, building user-adaptive systems can aid in providing each individual user with the interface that helps to best achieve the desired outcome. For example, online retailers now have the possibility to offer customized Web sites to individual customers, so as to meet each customer's specific needs. However, online retailers typically only have little data available to segment customers in real-time. In this study, we propose that observable usage data (such as click path data) can be used to distinguish female and male Web site visitors. Drawing on research in psychology and consumer behavior, we hypothesize that observable differences in Web surfing behavior can be indicative of a user's gender. Our results show that women tend to need less time and have shorter click paths than men in online product configuration tasks, and thus confirm the utility of using observable usage data to distinguish Web site visitors based on their gender.

Keywords: User Modeling, E-Commerce, Gender, Click Paths.

1 Introduction

Building user-adaptive systems can help achieve desired outcomes in various contexts, ranging from online retailing to workplace performance to sustained involvement in video games (Brusilovsky and Cooper, 2002; Charles et al., 2005; Randall et al., 2007). Similarly, for marketers, segmenting customers so as enable to precisely targeting individual customers with specific offers has long been considered the "holy grail" (Hoek, Gendall, and Esselemont, 1996; see also Smith, 1956), and advances in Internet technology have provided online retailers with various innovative ways to engage and interact with each individual customer; most notably, online retailers could present their customers custom-tailored Web sites "on the fly," in essence creating user-adaptive shopping environments for individual Web site visitors. In particular, online retailers could adapt what content to present depending on the user's gender (i.e. clothing for women or men) or adapt the structure of a Web site so as to meet a visitor's preferred individual information processing strategy (Brusilovsky, 1996; Brusilovsky and Cooper, 2002) or to attempt to generate additional sales.

Traditionally, marketers have attempted to use demographic data, psychographic data (e.g., values or attitudes), and other data to segment customers into groups of customers having similar characteristics, and provide tailored offers to different customer segments (Assael and Roscoe, 1976; Dickson and Ginter, 1987). In order to enable fine-grained customization, and to better target the most profitable customers, organizations are trying to reduce the size of identified customer segments; using sophisticated data mining techniques, many organizations are now attempting to predict the value and loyalty of each *individual* customer. Yet, segmenting Web site visitors in real-time, so as to dynamically adapt the interface to best meet each individual visitor's needs, presents considerable challenges, as many variables (especially demographic variables) are typically not known until a visitor becomes a registered user/customer. In traditional offline retail contexts, sales clerks can easily collect certain demographic variables, such as a person's age range or gender; often, cashiers ask customers for their ZIP (postal) code, which can be used to make inferences about other data such as education, income, or lifestyle. In online shopping contexts, collecting data about (non-registered) visitors is considerably more difficult. Online retailers could openly ask for demographic data during the registration or purchase process, but this approach may either not be possible due to privacy and data protection regulations, or it may cause customers to abandon the transactions due to privacy concerns (Lee, Ahn, and Bang, 2011); further, such data would only be available after a purchase (and typically only for registered customers, but not for non-registered visitors). Thus, while online retailers are able to make certain inferences (such as interests in a certain product category or literary genre) from browsing data (as for example Amazon.com, which suggests related products based on products viewed), they typically do not have the ability to pair this information with other data about the individual Web site visitor, and are thus unable to create comprehensive user models (see Wahlster and Kobsa, 1989). Yet, being able to segment visitors not only by browsing data, but also other demographic variables can have important practical implications, as developing integrated user models can help Web site designers to design user-adaptive systems that dynamically provide each individual visitor with an interface that best meets his or her needs.

To this end, drawing on research in human-computer interaction (HCI), information processing, and online consumer behavior, we aim to explore how click paths differ between users of different genders (a commonly used segmentation variable, see Meyers-Levy and Maheswaran, 1991; Simon, 2001) during the interaction with a Web site. In a preliminary study (Weinmann and Robra-Bissantz, 2012), we demonstrated that in the context of using a product configuration system for cars (a Web-based system enabling users to virtually assemble vehicles from given components such as engines, tires, and so on), the click paths differed significantly between male and female participants; specifically, we found that female participants tended to have shorter click paths than their male counterparts. In the current paper, we demonstrate that these findings hold in another, more gender-neutral context (vacation planning), and demonstrate that not only the length of a click path but also the time spent on a given task differs significantly between female and male Web site visitors. Next, we will briefly discuss relevant literature related to user modeling, click stream analysis, and mass customization (the context of our study), present our research hypotheses, and summarize the results of our earlier preliminary investigation. We then describe our current study and present the results of the empirical analysis. We conclude with a discussion of the implications for research and practice, and provide opportunities for future research.

2 Related Literature

2.1 User Modeling

The development of a user model, defined as "a knowledge source in a natural-language dialog system, which contains explicit assumptions on all aspects of the user that may be relevant to the dialog behavior of the system" (Wahlster and Kobsa, 1989, p. 6), is the basis for developing systems that can adapt to each individual user's particular needs. In other words, collecting data about a user can aid in developing a comprehensive user model, which, in turn, can be used to instruct the system how to adapt to the user's needs; for example, a user-adaptive system could provide a chat assistant to help inexperienced users (see Figure 1, Brusilovsky, 1996).

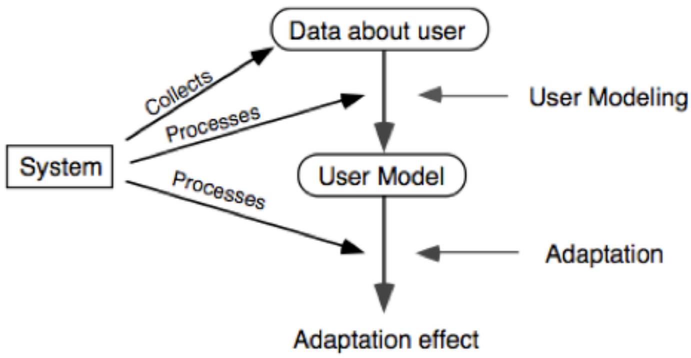

Figure 1. User Modeling Adaption Loop by Brusilovsky (1996)

Consequently, in order to represent a specific user by a user model, a system has to collect various types of data. Kobsa et al. (2001) distinguish between the following types of data that can be used for user modeling:

- User data: data about personal characteristics of the user, including demographics, knowledge, preferences, or skills
- Usage data: data about directly observable behavior, such as ratings, purchases, or usage regularities like action sequences that can be used to predict future actions or behavior
- Environment data: data about the location or computing environment.

While some of these data can be reliably captured (such as data about a user's computing environment or usage data), various data about the user cannot easily be captured, and have to be acquired explicitly (e.g., by asking) or implicitly (e.g., by inferring assumptions about user characteristics)(Chin, 1993; Hanani et al., 2001).

In online retailing, where the value of Web personalization is increasingly recognized (Kobsa, 2001), particular types of user data are likely of specific interest in constructing detailed user models. Specifically, literature in marketing suggests that demographics like age, gender, and income, as well as other psychographic variables are of particular importance when describing and segmenting users (Assael and Roscoe, 1976; Dickson and Ginter, 1987). Unfortunately, providers typically cannot directly observe most user data. However, directly observable usage data such as click paths (which Web site providers can easily capture; see Montgomery et al., 2004; Huang and Van Mieghem, 2011), can be used to infer certain user characteristics. Next, we will discuss click path analysis.

2.2 Click Path Analysis

For Web site providers, users' click paths constitute a valuable source of information. For example, organizations frequently analyze click paths to assess the performance of pages within their Web sites, to assess the pages' stickiness, or to find out which pages may contribute to customers abandoning the search or purchasing process (Walsh and Godfrey, 2000). Researchers have demonstrated that click paths (in terms of the sequence of pages visited) can be used to reliably forecast purchase conversion, intentions to revisit, or other intentions and behaviors (Montgomery et al., 2004). Relatedly, Huang and Van Mieghem (2011) demonstrated that the click streams on a company's non-transactional (or informational) Web site (such as in B2B contexts) can be predictive of customers' placing orders through other channels (such as sales people).

In addition, click paths can be used to make inferences about each individual visitor to a Web site. In attempting to infer users' personality types, Wen and Peng (2002) used artificial neural networks and demonstrated that it may be possible to distinguish personality types based on click paths. In sum, click paths have the potential to be used for a variety of purposes, and click paths might be a valuable source of user data in order to further complement user models. Yet, little research has attempted to distinguish users' demographic characteristics. As gender is a frequently used segmentation factor (Meyers-Levy and Maheswaran, 1991; Simon, 2001), we seek to analyze the potential of distinguishing users' gender from observable click paths as a first step in attempting to construct user models from click path data. In the next section, we will provide a brief overview of relevant literature related to mass customization and product configuration, the context of our study.

2.3 Mass Customization and Product Configuration

Online shopping has, among other innovations, enabled the concept of mass customization, allowing companies to provide custom-tailored products to individuals on a large scale (Pine, 1993). Mass customization works especially well for modular products or services (such as computers, cars, or even vacation packages) that can be easily assembled or combined in different ways (Duray, 2002). In order to make mass customization possible, online retailers typically implement decision support systems (or product configurators) that allow customers to select product or service attributes that meet their specific needs (Kamis, Koufaris, and Stern, 2008). Thus, mass customization takes the traditional concept of market segmentation a step further, in that not only product variations are marketed to several fairly homogeneous customer segments, but that products can be built that meet the exact needs of each individual customer (Gerards et al., 2011).

As product configuration systems are a key enabler of mass customization (Franke and Piller, 2003; Zipkin, 2001), allowing customers to configure products or services that meet their specific needs, much research has focused on the configuration process and its effects on purchase decisions, willingness to pay, or satisfaction with the configuration process (Dellaert and Stremersch, 2005; Franke and Piller, 2003; Huffman and Kahn, 2000). Yet, few studies have examined the possibility of tailoring the product configuration system *itself* to meet individual customers' needs (i.e., building user-adaptive systems). Most notably, Randall et al. (2007) demonstrated that depending on the users' expertise, different types of configuration systems (i.e., needs-based vs. parameter-based interfaces) can lead to different outcomes. While this highlights the importance of taking into account individual differences (i.e., building comprehensive user models) when attempting to design (adaptive) product configuration systems, to the best of our knowledge, no research has attempted to infer such individual differences during the use of the configuration process. In the next section we will discuss the role of gender and information processing, and present our research hypotheses.

3 Hypotheses Development

3.1 Gender Differences

Researchers from various fields have examined gender differences. In a seminal article, Maccoby and Jacklin (1974) reviewed literature on gender differences, and showed that males displayed more assertive, aggressive, and dominant personality traits as well as less anxiety than females. In addition, males and females display differences in information processing and evaluative judgments (see, e.g., Meyers-Levy and Maheswaran, 1991; Meyers-Levy and Sternthal, 1991). Consequently, gender is frequently used for customer segmentation, especially when designing marketing communications (e.g., Bhatnagar et al., 2004; Newman and Staelin, 1972), as segments based on gender are sufficiently large, easy to identify, and easy to access (Darley and Smith, 1995, see also Kim, Lehto, and Morrison, 2007); thus, gender is likely to be an important factor to consider when building user models for adaptive systems.

3.2 Gender Differences in Information Processing

Understanding the way people process information has important implications for designing user-adaptive systems, so as to create the intended effects (Jameson, 2003; Kobsa, 2001; Meyers-Levy and Maheswaran, 1991; Richards et al., 2010). Researchers in social psychology and marketing have demonstrated that females tend to be comprehensive information processors, whereas males tend to be selective processors (see Kim, Lehto, and Morrison, 2007 for a review): females tend to engage in greater elaboration, focus more on detailed message contents, and use all available information, including information from external sources; in contrast, males engage in less elaboration, using only subsets of the information available.

More specifically, Meyers-Levy and colleagues (Meyers-Levy, 1989; Meyers-Levy and Maheswaran, 1991; Meyers-Levy and Sternthal, 1991) argued that while men typically tend to use heuristics and base their processing primarily on readily available and salient information, women tend to make judgments only after all available information has been taken into consideration. In general, only if tasks prove to be too complex do men switch to elaborative information processing strategies (Meyers-Levy and Sternthal, 1991). As demonstrated by O'Donnell and Johnson (2001), these differences in processing strategies are likely to influence the efficiency in completing a task, especially for complex tasks. Given that complex tasks in general require more elaborative processing strategies (i.e., strategies typically used by females), females can be expected to be efficient in completing such tasks. In contrast, males (who are more used to employing heuristic elaboration strategies) can be expected to be less efficient in complex tasks (O'Donnell and Johnson, 2001).

These differences in efficiency in completing complex tasks suggest that in online shopping situations, differences in information processing should manifest in differences in click paths, since information is often presented on several pages. Especially when using product configurators (a relatively complex task typically requiring assembling products or services from different components), obtaining relevant information is likely to require elaborative processing strategies. Thus, we expect that women tend to be more efficient in such tasks, as evidenced in their click paths.

Relatedly, research in information systems suggests important differences between users of different genders. For example, Venkatesh and Morris (2000) and Venkatesh et al. (2003) demonstrated that gender plays a moderating role in technology acceptance. Further, according to Venkatesh et al.'s (2003) findings, performance expectancy is more salient to men, whereas effort expectancy is more salient to women, suggesting that women are likely to strive to minimize both the time spent and the number of pages visited during a configuration process:

H1: Women spend less time than men during online product configuration tasks.

H2: Women have shorter click paths than men in online product configuration tasks.

We conducted a preliminary test of H2 in the domain of cars (Weinmann and Robra-Bissantz, 2012); however, while we found preliminary support for this hypothesis, the results may have been biased by the domain. Thus, we performed a follow-up study in a more gender-neutral context. In the next section, we provide a brief summary of the preliminary study, followed by a discussion of our current study.

4 Summary Results of Preliminary Study

In a preliminary study (Weinmann and Robra-Bissantz, 2012) we tested the influence of gender on the length of a click path in online configuration tasks. We recruited 63 participants (mean age: 30.5 years; 46% female; 4.5h Internet use/day; 71.4% configuration experience) at a large German research university, and asked them to configure a car on www.volkswagen.de. The results of this preliminary study suggest that women indeed appeared to have significantly shorter click paths than men (for detailed results, please refer to Weinmann and Robra-Bissantz (2012)).

However, even though this study provided preliminary support for the hypothesis that women tend to be more efficient (and thus display shorter click paths), the task used in the preliminary study may have influenced the results: given that the task (configuring a car) may have been more interesting and intrinsically motivating for men, they may have spent more time assessing the available options, which would result in a longer click path. To further shed light on the relationship between gender and length of a click path, we intended to replicate our prior study in another, more gender-neutral domain, namely, vacation planning. In addition, this study allowed us to test the hypothesized relationship between gender and time spent on a configuration task. Next, we present this follow-up study.

5 Empirical Study

5.1 Design & Subjects

In order to test the hypotheses, we conducted a controlled laboratory study using 50 participants recruited at a large research university in Germany. After an initial survey to gather demographic data, we asked the participants to configure a vacation on the German site of the online travel agency Expedia (www.expedia.de). We measured time spent on the task, as well as the length of the click path. On average, each experiment lasted for approximately 30 minutes. We present a description of the data set in Table 2.

5.2 Task

We asked the participants to plan a vacation on the travel site www.expedia.de. We chose this task as it is perceived to be more gender-neutral (Kim et al., 2007; Sebastianelli et al., 2008) than the task used in our preliminary study (i.e., configuring a car). Whereas configuring a car is perceived to be a technical task and therefore might be more interesting for men (DeLoache et al., 2007), Kim et al. (2003) demonstrated that vacation planning on the Internet is perceived to be gender neutral or even in some aspects a favorable task for women. Specifically, we asked the participants to configure a vacation in Thailand (including return flights from Germany), subject to a number of constraints (such as budget, duration, hotel category, and distance to local attractions). We started recording click path data once the subjects entered the site, and stopped recording when the subjects reached the page asking for personal information; this constituted the end of the experiment.

5.3 Measures

Dependent Variables

Our dependent variables were the *length of the click path* and the *time* needed for the configuration task. Typically, the task of configuring a vacation on an online travel agency's Web site includes selecting a suitable flight (and choosing between different airlines, flight times, etc.) and hotel (considering location, description, etc.), with the different options presented on different pages. Using the usability software Morae (Version 3.2, www.techsmith.com/morae.html), we recorded the sequence of pages visited during the configuration task, and define length of click path as the sum of all pages visited during the task (Park, Yoon, and Lee, 2009). We also recorded the total time spent (in minutes) between accessing the Expedia Web site and completing the task.

Independent Variables

We observed each participant's gender, and coded women as 1 and men as 0.

Control Variables

In order to isolate the effects of gender on the length of the click path and time, we controlled for domain interest (measured on a 1-6 scale); as the task of vacation planning was intended to be gender neutral, we did not expect a significant relationship between gender and domain interest. Further, we controlled for age (in years), average Internet use (in hours/day), and configurator experience (yes/no).

6 Results

6.1 Model Specification

We performed an observational study under controlled conditions. To test the hypothesized influence of gender on time and length of click path, we conducted two separate regressions. Specifically, using SPSS 19.0, we estimated the following regressions:

(1) $\text{Time} = \alpha + \beta \cdot \text{Gender} + \text{Controls} + \varepsilon$

(2) $\text{Length of click path} = \alpha + \beta \cdot \text{Gender} + \text{Controls} + \varepsilon$

As women were coded as 1, a negative coefficient of gender would indicate that women spend less time on configuration tasks/ have shorter click paths than men, which would support the hypothesized relationships.

6.2 Findings

Table 2 presents a summary of the descriptive statistics of the participants; Table 3 presents the main results of the linear regressions.

Sample characteristic	**Unit**	**Female**		**Male**	
		Mean	Std. dev.	Mean	Std. dev.
Time	Minutes	9.90	(3.52)	11.63	(4.01)
Length of click path	Number Pages	25.25	(10.98)	32.63	(10.99)
Age	Years	24.42	(2.89)	26.43	(2.79)
Domain interest	1 – 6	2.95	(1.15)	2.90	(1.42)
Internet experience	Hours/day	3.72	(2.27)	5.73	(2.92)
Configurator experience	Yes = 1	.71	(.47)	.73	(.45)
N		20		30	

Table 2. Descriptive statistics

The results of the regressions (see Table 3) show that, when controlling for age, domain interest, average Internet use, and configurator experience, the coefficient of gender is approaching significance for time ($p < 0.10$; model 2), indicating that women spend less time than men in online configuration tasks, and providing tentative support for Hypothesis 1. Further, the coefficient of gender is significant for the length of click path ($p < 0.05$; model 4), supporting Hypothesis 2, that women have shorter click paths then men in online configuration tasks.

Dependent variable:	Time		Length of click path	
	(1)	(2)	(3)	(4)
Gender (1 = female)	-	-2.48*	-	-8.75**
Age	.25	.12	.99*	.54
Domain interest	.54	.54	-.99	-1.01
Internet use	-.30	-.43**	-.84	-1.32**
Configurator experience	-.71	-.55	5.81	6.38*
Constant	5.00	9.73	7.36	24.08
R^2	.11	.19	.14	.25
Adjusted R^2	.03	.09	.06	.16
N	50	50	50	50
Notes: * p < 0.10; ** p < 0.05				

Table 3. Results of the regression analysis

7 Discussion

7.1 Summary

The results of our current study confirm the findings of our preliminary study, and show that women tend to have shorter click paths and spend less time on online configuration tasks than men. Taken together, these two studies, using two different product domains (cars and vacations), provide support for our theoretical explanation that women tend to be more efficient in tasks requiring elaborate processing. Further, our study highlights the potential of using click path and time spent to infer demographic characteristics (in our case, gender) of a user, which provides another piece of information for generating comprehensive user models.

7.2 Limitations, Implications, and Directions for Future Research

As any study, this study is not without limitations. First, we used a student sample. Whereas this may have been problematic in the preliminary study (configuring a car), we believe that a vacation planning task is appropriate for our subject population. Second, our study setup did not allow us to directly test the underlying theoretical mechanisms. While we were able to show observable differences in behavior, future research should provide a stronger test of the underlying theoretical mechanisms for these differences. For example, future research could experimentally manipulate complexity, so as to test whether the observable differences indeed arise from different levels of task complexity and whether women are indeed more efficient in tasks requiring elaborative processing strategies, or could provide a stronger test of the relationship between gender and time spent. Further, we used a laboratory study, with a contrived task. As in any experiment, we have to deal with the tradeoff between internal and external validity. Whereas controlling for external factors helps to increase internal validity, it also decreases the generalizability of the results. By creating two tasks (across both studies) that are as realistic as possible (car and vacation configuration), we attempted to reduce the limits to generalizability. Nevertheless, future research could replicate this study in a field setting and test the effects of additional variables (such as expertise) on time and length of click path in online configuration tasks.

Notwithstanding these limitations, our study has some important implications for research and practice. First, our research demonstrates that there are observable differences between men and women when using online product configuration systems. Our results provide tentative support for our theoretical rationale that based on differences in information processing, females tend to be more efficient than males in completing complex tasks requiring elaborate processing.

Further, our results have important practical implications, especially for Web site designers striving to design user-adaptive systems. Integrated user models needed for designing user-adaptive systems consist of various different types of data (i.e., user, usage, and environment data), which can be combined to construct detailed user models (Kobsa, 2001); our findings can be regarded as an important component helping to create more detailed (or complete) user models, which, in turn, can help to design user-adaptive systems that precisely match each individual user. Similarly, online retailers attempt to segment customers into ever-smaller segments so as to better target marketing efforts and reach the most profitable customers. Yet, e-commerce providers still face the problem of not being able to observe some user characteristics. Our research has shown that there are observable differences in behavior, which can be used by online retailers to distinguish customers' gender. For example, different Web sites could be used to appeal to different genders or styles of processing. As we have focused on one particular piece of user data, future research maybe should attempt to find other ways observable usage data could be used to infer other types of user data (see also Wen and Peng, 2002).

8 Conclusion

User-adaptive systems can help to provide each individual user with the interface that best helps to achieve the desired outcomes. Similarly, e-commerce has grown rapidly in the past few years, and has provided retailers with various novel ways to engage and interact with their customers, such as providing their customers with custom-tailored Web sites on the fly, in essence creating individual shopping environments for individual customers. Building user-adaptive systems or providing such individualized interfaces necessitates creating comprehensive user models, so as to achieve the intended effects; however, while certain components of a user model are easily observable (e.g., usage data or environmental data), data about the users can typically not easily be captured.

In this study, we hypothesized that a user's gender can manifest in both the time and the length of the click path. Specifically, prior research in information processing suggests that based on women's tendency to engage in comprehensive processing and comparatively more effortful message elaboration (Meyers-Levy, 1988, 1989; Meyers-Levy and Sternthal, 1991), women should be more efficient in completing complex tasks and thus spend less time and display shorter click paths than men when using online product configuration systems. Results of a preliminary study in the context of cars suggested that women indeed have shorter click paths than men. We conducted a follow-up study in the context of vacation planning, and demonstrated that in this domain, too, women tended to spend less time and have shorter click paths when using product configuration systems.

Our findings have important implications for research and practice. From a theoretical perspective, we found that there are observable differences in behavior when interacting with online product configurators, which may be attributed to differences in type of processing (e.g., comprehensive vs. selective). From a practical perspective, the results highlight the possibilities of using relatively easily observable usage data to distinguish (typically unobservable) user data. Such information could prove tremendously useful for online retailers, who could dynamically present different users with different interfaces (i.e., user-adaptive systems), so as to provide the best interface for each individual user.

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